




The sspm R package: spatial surplus production models for the management of northern shrimp fisheries

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Statement of need

1. Population models, in particular fisheries productivity models, rarely integrate important spatially-structured ecosystem drivers
2. The Northern Shrimp stock in the Newfoundland and Labrador Shelves currently lacks a population model
3. Current SPM models are rarely spatially explicit and usually cannot account for relevant ecosystem drivers
4. Fisheries managers lack user-friendly, flexible tools to implement and apply SSPMs

Summary

Population modelling is an exercise of interest within environmental sciences and adjacent fields. Early population models such as the logistic model assumed that while the abundance of a population might change over time, the conditions governing parameters affecting that rate of change, such as the maximum rate of growth or the carrying capacity of the population, stay constant over time (Gotelli, 2008). Modern population models increasingly acknowledge the non-stationary nature of wild populations and work to incorporate environmental fluctuations into dynamic models (Thorson et al., 2017, 2015). Population models designed to answer applied resource management questions, such as fisheries stock models, increasingly address how the dynamics of stocks vary across space and time.

Resource managers are becoming increasingly interested in how variation in ecosystem factors such as predator abundance and abiotic variables impact the spatiotemporal variability of population parameters, such as productivity (Szuwalski & Hollowed, 2016; Zhang et al., 2021). Further, treating spatially structured stocks as single unstructured stocks can lead to substantially biased estimates of population change (Thorson et al., 2015). However, stock models that explicitly incorporate spatial dynamics and time-varying ecosystem variables are still rare in fisheries science, despite the push for more ecosystem-based management methods in fisheries management (Berkes, 2012; Crowder et al., 2008; Tam et al., 2017).

Surplus production models (SPMs) are one of the classic models used in fisheries and are based on modelling changes in the total biomass of a stock in a given location over time as a function of current stock abundance and fishing pressure (Walters et al., 2008). Classically, SPMs assume single unstructured stocks with purely logistic dynamics (Walters et al., 2008) and, as such, have been of limited use for modelling more complex stocks. They are useful in data-poor contexts where the age structure of the population is not accessible or when age

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or length structure do not change substantially over time (Prager, 1994; Punt, 2003). SPMs typically model spatially constant productivity. They also assume that populations are only affected by past abundance and fishing, which ignores stressors like climate change which affect growth rates independently of fishing pressure.

In the context of global warming and shifting ranges, fisheries productivity is likely to be a moving target (Karp et al., 2019), and managers need better methods that account for varying productivity (Szuwalski & Hollowed, 2016). The Northern Shrimp (*Pandalus borealis*) in the Newfoundland and Labrador Shelves, which has undergone several periods of large-scale biomass change in the last two decades, despite a relatively constant harvest regime, is a prime example of a population thought to be affected by environmental conditions (DFO, 2019). These populations currently lack a population model to understand the drivers of this change and to predict how fishing pressure and changing environmental conditions may affect future abundance.

Population models like SPMs usually fall under the two following categories: process-based and statistical models. Process-based models often rely on differential or difference equations and are based on replicating the underlying processes (e.g., predation, recruitment, dispersal) driving population dynamics. Statistical models instead fit a regression model to time series of population abundances, abundance indices, or productivities, with some assumed error distribution for variation around predictions.

We have chosen a statistical approach to fitting SPMs. Statistical models allow for estimation of parameter uncertainty and ranges of model predictions and for flexibly incorporating potential ecosystem drivers into models (Plagányi et al., 2014). Statistical models also allow for straightforward estimation of spatial variation in population parameters such as maximum productivity or density dependence from data, in the absence of theory predicting how these parameters should vary.

In this paper, we use a statistical approach to fitting SPMs using Generalized Additive Models (GAMS), estimated using the mgcv R package (Wood, 2017) as the backend. We apply this approach to the population of Northern Shrimp of the Newfoundland and Labrador Shelves, leveraging the smoothing properties of GAMs to account for varying productivity across time and space. The resulting model is a spatial SPM (SSPM), implemented via an R package: `sspm`.

While the initial application of this model was modelling Newfoundland and Labrador Northern Shrimp stocks (Pedersen et al., 2022), the R package `sspm` is designed to make spatially-explicit surplus production models (SSPM) easier to estimate and apply to any spatially structured stock. The package uses GAMs to smooth spatiotemporally varying biomass, and to fit SSPMs based on changes in fitted biomass, observed catch, and spatially structured environmental predictors. It includes a range of features to manipulate harvest and biomass data. Those features are organized in a stepwise workflow, whose implementation is described in more detail in Figure 1 and in the next section.

Although it was developed in a fisheries context, the package is suited to model spatially-structured population dynamics in general.

Package design

The package follows an object oriented design, making use of the S4 class systems to model a stepwise workflow: (Figure 1).

The key workflow steps are:

- Discretization and aggregation of spatially structured observations into discrete patches, with a range of methods of discretization (random or custom sampling, Voronoi tessellation, or Delaunay triangulation).

- 87 1. Provided boundary data in the form of a shapefile is converted into a `sspm_boundary`
- 88 object using `spm_as_boundary()` to define the boundary/region of interest.
- 89 2. The region within the boundary is discretized into patches with the
- 90 `spm_discretize()` function, creating a `sspm_discrete_boundary` object.
- 91 ■ Spatiotemporal smoothing of biomass and environmental predictors using GAMs.
- 92 3. The `spm_as_dataset()` function turns user-provided data frames of raw observa-
- 93 tions into `sspm_dataset` objects that explicitly track locations, data types, and
- 94 aggregation scales for each input. `sspm` recognizes three types of data: **trawl**
- 95 (i.e. biomass estimates from scientific surveys), **predictors**, and **catch** (i.e., harvest).
- 96 4. The `spm_smooth()` function use spatiotemporal GAMs to smooth the biomass and
- 97 predictor data, based on the spatial structure from `sspm_discrete_boundary`. The
- 98 user specifies a GAM formula with custom smooth terms. The output is another
- 99 `sspm_dataset` object with a `smoothed_data` slot which contains the smoothed
- 100 predictions for all patches.
- 101 ■ Computation of surplus productivity based on biomass density and fishing effort.
- 102 5. The `spm_aggregate_catch()` function aggregates catch into patches and years and
- 103 calculates patch-specific productivity for each year as the ratio of estimated biomass
- 104 density plus catch from the next year divided by estimated biomass density of the
- 105 current year. The result is returned as a `sspm_dataset`.
- 106 6. The `sspm()` function combines productivity and predictor datasets into a single
- 107 dataset. Additionally, the user may create lagged versions of predictors with
- 108 `spm_lag()` and split data into testing and training sets for model validation with
- 109 `spm_split()` at this stage.
- 110 ■ Fitting of SSPMs to productivity estimates with GAMs.
- 111 7. The `spm()` function is used to fit a SSPM model to the output of step 6, using a
- 112 GAM model with custom syntax able to model a range of SSPMs. The output is
- 113 an `sspm` object.
- 114 ■ Visualization of results, and one-step-ahead projections of biomass for model validation
- 115 and scenario-based predictions.
- 116 8. Plots can be generated with the `plot()` method. Predictions from the fitted model
- 117 can be obtained using the built-in `predict()` method, including confidence and
- 118 prediction intervals

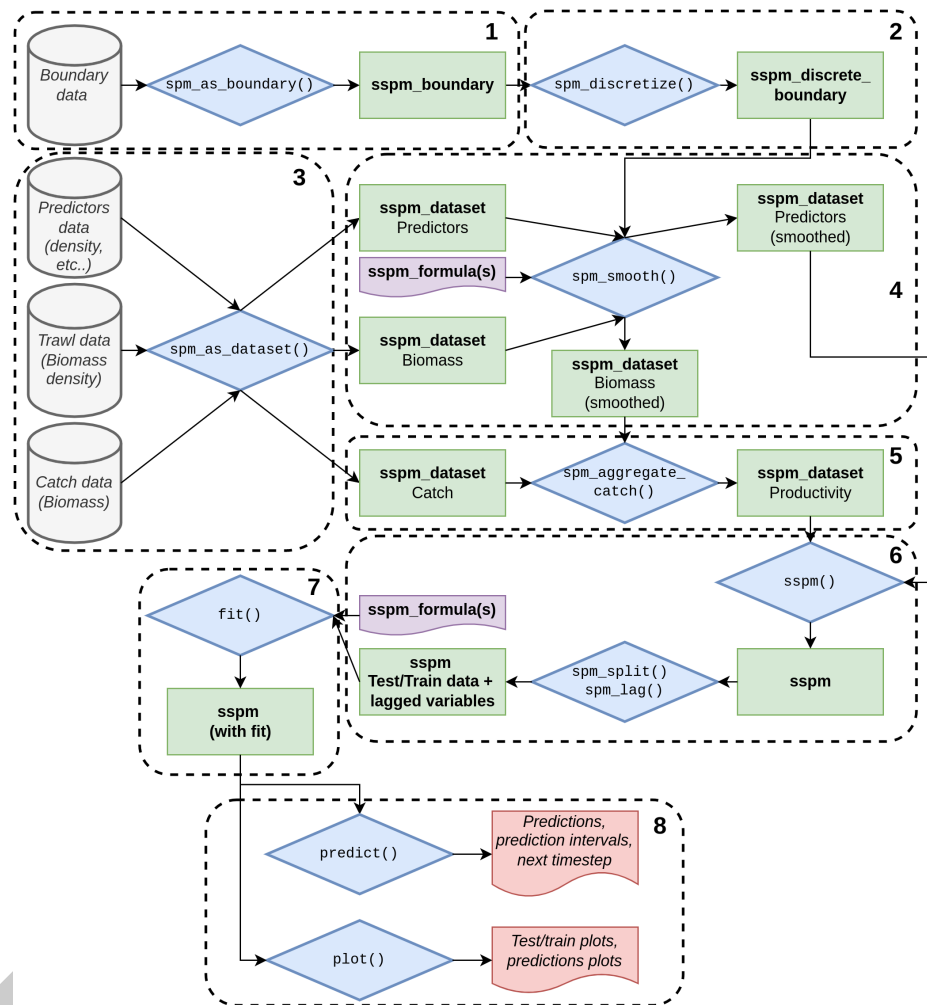


Figure 1: The sspm workflow. Gray cylinders represent raw, unprocessed sources of data. Each blue diamond shape represents a function processing a raw input and validating it, or producing an intermediate package object, represented as a green object. Secondary objects like formulas, which must be created by the user, are represented by a purple document shape. Finally, outputs are represented by a red document shape. The steps of the workflow as described above are denoted by dotted lines and corresponding step number.

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References

- Berkes, F. (2012). Implementing ecosystem-based management: Evolution or revolution? *Fish and Fisheries*, 13(4), 465–476. <https://doi.org/10.1111/j.1467-2979.2011.00452.x>
- Crowder, L. B., Hazen, E. L., Avissar, N., Bjorkland, R., Latanich, C., & Ogburn, M. B. (2008). The impacts of fisheries on marine ecosystems and the transition to ecosystem-based management. *Annual Review of Ecology, Evolution, and Systematics*, 39(1), 259–278.

- 130 <https://doi.org/10.1146/annurev.ecolsys.39.110707.173406>
- 131 DFO. (2019). *An assessment of Northern Shrimp (pandalus borealis) in Shrimp Fishing Areas*
 132 *4–6 and of Striped Shrimp (pandalus montagui) in shrimp fishing area 4 in 2018* (Technical
 133 Report No. 2019/027; p. 23). Canadian Science Advisory Secretariat (CSAS).
- 134 Gotelli, N. J. (2008). *A Primer of Ecology* (Fourth Edition). Oxford University Press.
 135 ISBN: 978-0-87893-318-1
- 136 Karp, M. A., Peterson, J. O., Lynch, P. D., Griffis, R. B., Adams, C. F., Arnold, W. S.,
 137 Barnett, L. A. K., deReynier, Y., DiCosimo, J., Fenske, K. H., Gaichas, S. K., Hollowed, A.,
 138 Holsman, K., Karnauskas, M., Kobayashi, D., Leising, A., Manderson, J. P., McClure, M.,
 139 Morrison, W. E., ... Link, J. S. (2019). Accounting for shifting distributions and changing
 140 productivity in the development of scientific advice for fishery management. *ICES Journal*
 141 *of Marine Science*, 76, 1305–1315. <https://doi.org/10.1093/icesjms/fsz048>
- 142 Pedersen, E. J., Skanes, K., Le Corre, N., Koen-Alonso, M., & Baker, K. (2022). *A new spatial*
 143 *ecosystem-based surplus production model for SFA 4-6 Northern Shrimp* (pp. in press)
 144 [Canadian Science Advisory Secretariat (CSAS) Research Document].
- 145 Plagányi, É. E., Punt, A. E., Hillary, R., Morello, E. B., Thébaud, O., Hutton, T., Pillans, R.
 146 D., Thorson, J. T., Fulton, E. A., Smith, A. D. M., Smith, F., Bayliss, P., Haywood, M.,
 147 Lyne, V., & Rothlisberg, P. C. (2014). Multispecies fisheries management and conservation:
 148 Tactical applications using models of intermediate complexity. *Fish and Fisheries*, 15(1),
 149 1–22. <https://doi.org/10.1111/j.1467-2979.2012.00488.x>
- 150 Prager, M. H. (1994). A suite of extensions to a nonequilibrium surplus-production. *Fishery*
 151 *Bulletin - National Oceanic and Atmospheric Administration*, 92, 374–389.
- 152 Punt, A. E. (2003). Extending production models to include process error in the population
 153 dynamics. *Canadian Journal of Fisheries and Aquatic Sciences*, 60(10), 1217–1228.
 154 <https://doi.org/10.1139/f03-105>
- 155 Szuwalski, C. S., & Hollowed, A. B. (2016). Climate change and non-stationary population
 156 processes in fisheries management. *ICES Journal of Marine Science*, 73(5), 1297–1305.
 157 <https://doi.org/10.1093/icesjms/fsv229>
- 158 Tam, J. C., Link, J. S., Rossberg, A. G., Rogers, S. I., Levin, P. S., Rochet, M.-J., Bundy, A.,
 159 Belgrano, A., Libralato, S., Tomczak, M., Wolfshaar, K. van de, Pranovi, F., Gorokhova,
 160 E., Large, S. I., Niquil, N., Greenstreet, S. P. R., Druon, J.-N., Lesutiene, J., Johansen, M.,
 161 ... Rindorf, A. (2017). Towards ecosystem-based management: Identifying operational food-
 162 web indicators for marine ecosystems. *ICES Journal of Marine Science*, 74(7), 2040–2052.
 163 <https://doi.org/10.1093/icesjms/fsw230>
- 164 Thorson, J. T., Jannot, J., & Somers, K. (2017). Using spatio-temporal models of population
 165 growth and movement to monitor overlap between human impacts and fish populations.
 166 *Journal of Applied Ecology*, 54(2), 577–587. <https://doi.org/10.1111/1365-2664.12664>
- 167 Thorson, J. T., Skaug, H. J., Kristensen, K., Shelton, A. O., Ward, E. J., Harms, J. H., &
 168 Benante, J. A. (2015). The importance of spatial models for estimating the strength of
 169 density dependence. *Ecology*, 96(5), 1202–1212. <https://doi.org/10.1890/14-0739.1>
- 170 Walters, C. J., Hilborn, R., & Christensen, V. (2008). Surplus production dynamics in declining
 171 and recovering fish populations. *Canadian Journal of Fisheries and Aquatic Sciences*,
 172 65(11), 2536–2551. <https://doi.org/10.1139/F08-170>
- 173 Wood, S. N. (2017). *Generalized Additive Models: An Introduction with R, 2nd Edition* (2nd
 174 ed.). CRC Press. ISBN: 978-1-4987-2837-9
- 175 Zhang, F., Reid, K. B., & Nudds, T. D. (2021). The longer the better? Trade-offs in
 176 fisheries stock assessment in dynamic ecosystems. *Fish and Fisheries*, 22(4), 789–797.
 177 <https://doi.org/10.1111/faf.12550>